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European J. Industrial Engineering, Vol. 11, No. 2, 2017 205

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Abstract: This paper presents a hybrid method to determine the optimum combination of product form features in Kansei engineering. This method integrates the Taguchi method and grey relational analysis (GRA) coupled with principal component analysis (PCA). Experiments are performed on a variety of passenger car form designs. The Taguchi's L_{27} OA is chosen to design the experiments and to generate the car silhouettes as design samples. GRA is used to solve the multi-response optimisation problem, while PCA is used to assign the weighting values of relevant Kansei responses. The results show that the hybrid method was able to solve the complexity trade-off encountered in the decision-making process of multi-response optimisation using an economical and effective experimental design method. The method also has the capability in determining the optimum combination of product form features and generating an optimised car form design which accommodates the multi-Kansei need of consumers in a systematic manner. [Submitted: 28 June 2014 ; Revised 5 March 2016; Accepted: 28 September 2016]

Keywords: Taguchi method; TM; grey relation analysis; principal component analysis; PCA; multi-response decision-making; product form design; Kansei engineering.

Reference to this paper should be made as follows: Sutono, S.B., Abdul-Rashid, S.H., Taha, Z., Subagyo and Aoyama, H. (2017) 'Integration of grey-based Taguchi method and principal component analysis for multi-response decision-making in Kansei engineering', *European J. Industrial Engineering*, Vol. 11, No. 2, pp.205–227.

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1 Introduction

The appearance and aesthetics of a product are among the essential aspects that influence a consumer's buying decision. When it comes to buying decisions, consumers tend to follow their feelings, emotions and perceptions, and they may seek for something more than what product designers have anticipated. It is generally known that products should be designed in order to fulfil the needs of the consumer. Thus, consumers' aesthetics and emotional requirements (i.e., Kansei needs) have become essential in product design. A number of systematic product design studies have been carried out over the years to gain a better understanding on the subjective perception of consumers. A prominent study in product design is Kansei engineering (KE) (Nagamachi, 2002, 2008), which is considered as one of the most reliable and useful methods in dealing with the aesthetics and emotional needs of consumers (Chen et al., 2008).

KE is a methodology that unites Kansei with engineering discipline, in which the development of products that bring happiness and satisfaction to humans is performed technologically, by analysing human emotions and incorporating them into the product design. Kansei is a Japanese word which can be literally translated as feeling, image, emotion, affection, sense or impression (Nagamachi, 2011). Schütte et al. (2004) defined KE as a proactive product development methodology which explores the consumers' impressions, feelings and demands about existing products or concepts in a systematic manner and translating them into design solutions and concrete design parameters. A more detailed treatment on the concepts, as well as methods and tools used in KE has been elaborated by Schütte et al. (2004). KE has been adopted successfully in various design applications such as in the development of mobile phones (Lai et al., 2006; Roy et al., 2009), home appliances (Demirtas et al., 2009), machine tools (Mondragón et al., 2005), material design (Karana et al., 2009), trade show booths (Huang et al., 2011), urban planning (Llinares and Page, 2008) and traditional crafts (Yan et al., 2012).

The consumers' Kansei perceptions create a multi-response problem which is important for decision-making process in KE. This is due to the fact that transformation of the consumers' Kansei perceptions into optimum product design features should be considered as a multi-response decision-making process. Multi-response decision-making is a highly complex process, which is resource and time-intensive, and involves high costs (Schütte et al., 2004). Therefore, the development of a systematic approach to determine the optimum product design features is a challenging task in KE. Several attempts have been made to develop systematic optimisation methods based on robust design methods. One such example of a robust design method is the Taguchi method (TM), which is based on simple experimental designs that focuses on time and cost reduction in evaluation experiments in order to determine the optimum combination of product form features. Lai et al. (2005) and Sutono et al. (2012) have used TM and analysis of variance (ANOVA) to study the effect of design parameters on the optimum combinations of product forms in KE. More recently, Oztekin et al. (2013) proposed that Taguchi-based approaches are simple, feasible and versatile to determine the combinations of product design parameters by considering the consumers' impression and feelings during the product design stage. However, these studies have primary focused on implementing TM to attain the optimum design solution of Kansei responses in which the problem is basically a single-response optimisation decision-making problem. This is understandable as TM was originally designed to handle optimisation problems of a single performance characteristic (El-Taweel and El-Axir, 2009; Wu, 2004). Consequently, the application of TM to handle optimisation problems with multiple performance characteristics is certainly more complicated. Optimisation of Kansei responses in a segregated manner may lead to a serious conflict of the feature's setting in a multi-response problem (Hsieh et al., 2005). Hence, the goal of this study is to extend the TM for a multi-response decision-making problem in KE by integrating TM with a multi-response decision-making technique.

There are several methods for multi-response decision-making, such as the technique for order preference by similarity to ideal solution (TOPSIS), elimination and choice translating reality (ELECTRE), preference ranking organisation method for enrichment evaluation (PROMETHEE) and grey relational analysis (GRA). In a recent development, Wang et al. (2014) combined the TOPSIS method with experimental design and Chebyshev regression to solve multi-criteria decision-making problem of equipment selection in a manufacturing environment. Meanwhile, Ding et al. (2014) have proposed a multi-criteria decision-making model by integrating the TOPSIS and FMEA to select the optimal maintenance policy systematically. Hashemi et al. (2014) have proposed the extended ELECTRE method based on black number under ambiguous environment in order to deal with supplier selection problems. In addition, Corrente et al. (2014) have developed a methodology permitting consideration for interactions between criteria in the PROMETHEE method. Among these multi-response decision-making methods, the GRA is chosen for this study because of its simplicity and straightforwardness in mathematical calculation, as well as prioritisation (Kuo et al., 2008; Wu, 2002) and stability as an effective method in solving complex decision-making optimisation problems which outperforms other popular methods (Wang et al., 2013).

A number of studies have proposed the use of TM in combination with GRA for a variety of applications. This method has been applied to determine the optimum selection of process parameters for various machining processes such as macro-EDM (Meena and Azad, 2012), wire-EDM (Rajyalakshmi and Ramaiah, 2013), high-speed turning (Pawade and Joshi, 2011), high-speed end milling (Kopac and Krajnik, 2007), micro-milling (Kuram and Ozcelik, 2013), laser transmission welding process of thermoplastics (Acherjee et al., 2011), and drilling (Prasanna et al., 2014). However, it was noted that the assignments of the weighting values of each performance characteristic were highly subjective in all of these studies and have been solely based on the estimation of the respective researchers. The methods presented in such studies are incapable of revealing the relative importance of various performance characteristics in an objective manner.

Hence, in this paper, the principal component analysis (PCA) is integrated with TM and GRA to overcome such limitations of previous methods.

In recent studies, PCA has been steadily incorporated with TM and GRA to determine the optimum selection of process parameters in various machining processes such as welding (Adalarasan et al., 2014), CNC end milling (Lu et al., 2009), in-feed centreless cylindrical grinding (Siddiquee et al., 2010), and colour filter manufacturing (Chiang and Hsieh, 2009). In addition, Wang and Wang (2013) coupled PCA with GRA to solve an information redundancy problem resulting from multiple parameters, and have used the method to identify wear particles quickly and accurately. Although this method offers a number of benefits, there is yet to be any studies of its implementation in the area of KE. Thus, this method is proposed to solve the multi-response optimisation decision-making problem in KE to determine the optimum combination of product form features. In line with these motivations, a hybrid method integrating TM, GRA and PCA is proposed in this paper, and is given the name 'grey PCA-based TM'. The grey PCA-based TM can be used for addressing the multi-response optimisation decision-making problem to determine the optimum combination of product form features. The method is also able to generate an optimised product form design based on the various Kansei responses.

This paper is organised with a brief introduction given in Section 1, which includes the motivation and objective of this study. The KE procedure is presented in Section 2 and the grey PCA-based TM is described in Section 3. The results are discussed in detail in Section 4 and finally, the concluding remarks of this study are presented in Section 5.

2 KE procedure

A case study on passenger car form designs was chosen as the domain of investigation in this study. This case study was selected to demonstrate the application of grey PCA-based TM in determining the optimum combination of car form features based on multiple Kansei responses. An evaluation survey on car form samples was carried out based on consumers' subjective perception, which in this case, was specifically for the consumers in Malaysia.

The KE experimental procedure is outlined as follows:

1 the representative Kansei words which would be used as the Kansei responses were identified and selected

2 the design parameters or form features were identified and their levels were set for the Taguchi's orthogonal array (OA) experimental design

3 the appropriate Taguchi's OA was adopted and the form features were assigned to the OA

4 the design samples were generated based on the selected OA

5 the evaluation experiment was conducted for each design sample based on the representative Kansei responses

6 the experimental results were analysed.

2.1 Representative Kansei responses

A total of 16 initial Kansei word pairs were selected to describe the consumers' Kansei responses on car forms, as shown in Table 1. These word pairs were shortlisted by eliminating the adjectives gathered from relevant KE literatures, car magazines and the internet based on the relationship and similarities in the definitions (i.e., synonyms). The initial Kansei words were reduced according to their importance and relevance to the study, resulting in the representative Kansei responses. The number of representative Kansei responses used in the experiment should be less or equal to seven to simplify analysis and assure reasonable consistency (Saaty and Ozdemir, 2003). The final sets of representative Kansei word pairs were then determined using factor analysis and cluster analysis, and are listed in Table 2.

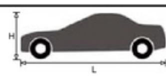
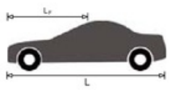
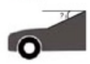
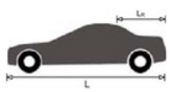
Table 1 Initial Kansei word pairs

No.	*Kansei word pairs*
1	Elegant – inelegant
2	Stylish – unstylish
3	Youthful – oldish
4	Sleek – lustreless
5	Modern – ordinary
6	Powerful – powerless
7	Rugged – fragile
8	Spacious – confined
9	Cute – not cute
10	Sporty – not sporty
11	Formal – casual
12	Grand – not grand
13	Streamlined – not streamlined
14	Classic – poor
15	Bold – plain
16	Masculine – feminine

Table 2 Representative Kansei word pairs used as Kansei responses

Kansei word cluster	*Kansei word pairs*	*Kansei response*
1	Modern – ordinary	Modern
2	Elegant – inelegant	Elegant
3	Sporty – not sporty	Sporty
4	Youthful – oldish	Youthful

Table 3 Car form features and corresponding levels

Symbol		*Form feature*	*Feature level*		
			1	*2*	*3*
A		Ratio of car height to car length [H/L]	0.326	0.273	0.220
B		Ratio of fore region length to overall length [L_F/L]	0.360	0.425	0.490
C		Ratio of front height to overall height [H_F/H]	0.600	0.540	0.480
D		Gradient of front bumper [θ_1]	0	15	30
E		Gradient of hood [θ_2]	0	3	6
F		Gradient of A-pillar [θ_3]	20	25	30
G		Ratio of rear region length to overall length [L_R/L]	0.140	0.235	0.330
H		Ratio of rear region height to overall height [H_R/H]	0.710	0.680	0.650
I		Gradient of C-pillar [θ_4]	20.	30	40
J		Gradient of rear bumper [θ_5]	–16	0	16
K		Gradient of trunk [θ_6]	2	4	6
L		Gradient of rear fender bottom [θ_7]	0	6	12
M		Gradient from side top [θ_8]	14.	22	30

2.2 *Product form features*

The product form features which will evoke the consumers' Kansei responses are defined as the control factors in the Taguchi experiments. Past studies related to KE and car design were first reviewed to identify the appropriate form features for car design (Lai et al., 2005; Nordgren, 2007). The form features which would most likely influence the consumers' Kansei responses were then identified. A total of 13 form features were adapted and modified from Lai et al. (2005) and Nordgren (2007), and their corresponding level settings are presented in Table 3. The position of the form features with respect to the overall car is also shown in Table 3. The insignificant features are kept fixed and excluded from the form feature settings for impression effect evaluation.

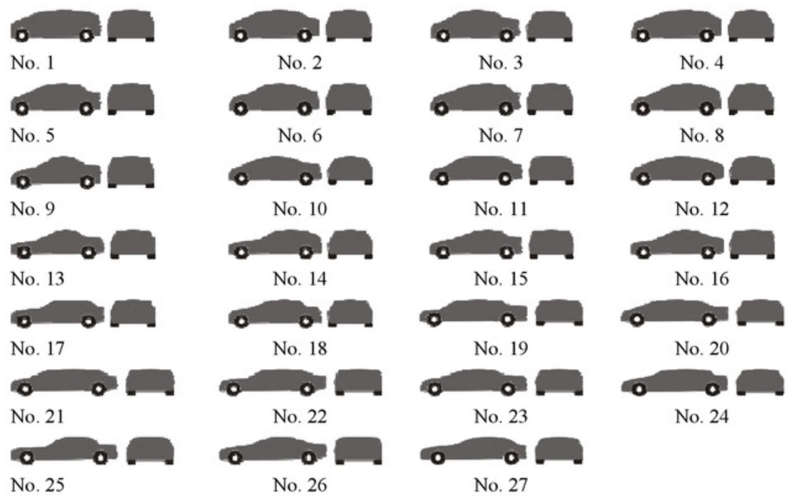
2.3 Taguchi experimental design and samples

The car form design samples were generated using Taguchi's OA. The Taguchi experiments chosen for this case study should accommodate 13 form features with three level settings, as shown in Table 3. The full factorial of this combination experiment would require up to 1,594,323 (313) design samples. However, the number of experiments can be reduced effectively by using an OA. The Taguchi's L_{27} OA was adopted due to the number of form features and their corresponding levels, and the experimental layout is shown in Table 4. The level data of each form feature in the orthogonal table is used to generate a basic car form design (silhouette) for Kansei response evaluation. A total of 27 combinative design samples were generated using Taguchi's L_{27} OA and are shown in Figure 1.

Table 4 Experimental design layout using Taguchi's L_{27} OA

Experiment no.	*Level of design parameter*												
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Figure 1 Combinative car form design samples



2.4 Evaluation experiment for Kansei response measurement

A survey was conducted using questionnaire approach to measure the Kansei responses for car form design. The questionnaire consists of four representative Kansei words which describe the consumers' subjective Kansei responses as well as 27 combinative car form design samples generated using the Taguchi's OA. A total of 219 Malaysian respondents comprising 97 males (44.3%) and 122 females (55.7%) with ages ranging from 18–56 years old had participated in the survey. The respondents were requested to evaluate each design sample with respect to the Kansei responses using a five-point Likert scale. The questionnaire was designed based on the semantic differential method (Nagamachi, 2011). The semantic differential method is a measurement tool frequently used in product design, especially KE, in order to measure the affective and emotional value of a product. The average data scores of the subjects' evaluation for each design sample and Kansei responses were calculated to obtain a final utility rating. The data obtained from the survey were further processed using the grey PCA-based TM described in Section 3.

3 Grey PCA-based TM

Grey PCA-based TM is used to solve multi-response optimisation decision-making problem in determining the optimum combination of car form features based on multiple Kansei responses. Using this method, TM is firstly used to transform the Kansei responses obtained into S/N ratio of multiple performance characteristics. Then, GRA is utilised to convert the multiple performance characteristics into a single performance characteristic index, namely the grey relational grade (GRG), to simplify the optimisation process. In the GRA, the S/N ratio are initially normalised into comparability sequence known as grey relational generation. The grey relational coefficient (GRC) can then be calculated from the normalised data to determine the degree of closeness between the desired and comparability sequences. The weighting values corresponding to each performance characteristic are then determined using PCA. The GRG is calculated by integrating these GRCs and weighting values to give the overall evaluation of the multiple performance response. Thus, the seemingly complicated multiple performance characteristics can be optimised by converting them into the optimisation of a single GRG. Finally, the Taguchi analysis will indicate the optimum combination of product form features based on the form features level with the highest GRG, which is identified based on the Taguchi analysis. ANOVA can also be conducted to evaluate the effectiveness and relative importance of each form feature.

The process details to determine the optimum combination of product form features using grey PCA-based TM are presented in the following sections.

3.1 Taguchi method

The TM was developed by Genichi Taguchi and has been accepted as a simple and effective solution for parameter design and experimental planning in designing and improving product quality. The OAs from experimental design theory are utilised to examine a large number of variables with a small number of experiments. In essence, TM is based on OA, loss function and the signal-to-noise (S/N) ratio (Taguchi et al., 2005). An OA is first defined based on a number of design parameters and their levels. The deviation between the experimental and the desired value is then calculated by defining a loss function. Finally, the S/N ratio is determined by converting the loss function value and is used to determine the performance characteristic. There are three types of the performance characteristic involved in the S/N ratio analysis, i.e., the nominal-the-best, the smaller-the-better and the larger-the-better.

In this paper, the S/N ratio of the larger-the-better performance characteristic is applied for each Kansei response. The S/N ratio η_{ij} of the larger-the-better characteristic is given by:

$$\eta_{ij} = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{ij}^2}\right) \quad (1)$$

where y_{ij} is the evaluation value of the i^{th} experiment at the j^{th} subject, and n is the number of subjects.

The mean and S/N ratio for each combinative design sample with respect to the four representative Kansei responses in Taguchi experiments, calculated using equation (1), are presented in Table 5.

3.2 Grey relational analysis

GRA is a part of grey system theory developed by Deng (1982). GRA is an effective method for determination of uncertainties in a system model, and therefore assists users in predictions and decision-making. GRA examines the degree of similarity between each alternative candidate solution in a multiple attributes problem and the ideal alternative solution. All alternative candidate solutions are evaluated based on the relational grade of discrete data sequences (Deng, 1989). An alternative candidate solution with a higher relational grade indicates that the candidate solution has a higher similarity to the ideal alternative solution which has the best performance. Thus, the best candidate solution will be preserved.

Table 5 Results of mean and S/N ratio calculation

Exp. no.	*Elegant*		*Youthful*		*Modern*		*Sporty*	
	Mean	*S/N ratio*	*Mean*	*S/N ratio*	*Mean*	*S/N ratio*	*Mean*	*S/N ratio*
1	3.009	6.113	1.776	2.158	2.712	6.772	1.712	2.032
2	2.849	6.529	2.694	5.681	2.393	5.632	2.073	3.522
3	2.534	5.698	3.110	6.945	2.900	7.424	2.776	5.640
4	3.256	7.867	3.023	6.489	3.128	8.086	3.110	6.492
5	2.685	5.910	3.338	7.458	3.205	7.544	2.530	4.959
6	3.311	8.344	3.397	8.361	2.932	7.343	2.749	6.443
7	2.895	7.127	3.740	9.538	3.256	8.837	3.279	8.937
8	3.342	8.279	3.603	9.199	3.429	9.009	3.507	9.099
9	3.196	7.347	3.489	8.137	2.763	6.551	2.808	6.503
10	3.187	6.988	1.822	2.224	3.237	7.092	2.826	5.558
11	2.963	6.493	1.489	1.279	2.233	3.783	1.425	1.160
12	3.388	7.016	2.178	3.579	3.694	7.345	2.635	4.700
13	3.685	8.590	3.626	8.550	3.840	8.838	3.224	8.374
14	2.731	4.953	1.881	2.414	2.740	5.095	2.945	5.312
15	3.767	9.760	3.269	8.309	4.219	10.415	3.374	8.702
16	3.758	9.813	2.703	5.917	3.831	9.970	2.959	7.728
17	2.813	6.559	2.548	4.979	2.868	6.550	2.995	6.459
18	3.233	8.610	3.548	8.497	3.877	9.464	4.027	8.815
19	3.146	6.546	1.416	1.164	2.384	4.060	1.507	1.417
20	3.507	7.727	1.795	2.241	3.356	7.413	2.836	5.279
21	3.224	6.867	1.457	1.226	2.342	4.301	1.543	1.551
22	2.936	6.447	2.128	3.196	2.790	5.822	2.616	5.087
23	4.128	10.282	2.384	4.244	3.858	9.406	2.836	6.235
24	3.000	6.434	1.881	2.537	2.676	5.471	2.374	3.882
25	3.274	6.778	2.114	3.154	2.315	3.955	2.826	5.456
26	4.365	10.664	3.046	7.314	3.900	10.019	3.365	8.743
27	3.137	7.463	2.635	5.323	3.329	7.867	3.329	7.649

The procedural steps in GRA, as related by Kuo et al. (2008), are described in the following sections:

3.2.1 Grey relational generation

The first step in GRA is the grey relational generation in which the data is processed to prevent erroneous results which can occur if the factor goals and the direction of the attribute data are different. Data related to a group of sequences must be normalised into the comparability sequences. There are three types of normalised data transformation, namely, the smaller-the-better, the larger-the-better and the nominal-the-best.

In this study, the S/N ratio for each combinative design sample based on the four representative Kansei responses are first transformed into comparable sequences through data normalisation. The normalised data of the larger-the-better transformation is adopted during this process and calculated using the following equation:

$$x_{ij} = \frac{\eta_{ij} - \min \eta_{ij}}{\max \eta_{ij} - \min \eta_{ij}} \tag{2}$$

where x_{ij} is the normalised S/N ratio and η_{ij} is the S/N ratio for the original sequence of the i^{th} alternative (experiment) at the j^{th} attribute (response), in which $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

The results of grey relational generation for each combinative design sample with respect to the four Kansei responses calculated using equation (2) is presented in Table 6.

Table 6 Sequences after data processing and deviation sequences

Exp. no.	*Sequences after data processing*				*Deviation sequences (Δ_{ij})*			
	Elegant	*Youthful*	*Modern*	*Sporty*	*Elegant*	*Youthful*	*Modern*	*Sporty*
X_0	*1*	*1*	*1*	*1*				
1	0.2030	0.1187	0.4508	0.1099	0.7970	0.8813	0.5492	0.8901
2	0.2760	0.5394	0.2788	0.2975	0.7240	0.4606	0.7212	0.7025
3	0.1305	0.6903	0.5491	0.5643	0.8695	0.3097	0.4509	0.4357
4	0.5102	0.6359	0.6489	0.6716	0.4898	0.3641	0.3511	0.3284
5	0.1675	0.7516	0.5672	0.4785	0.8325	0.2484	0.4328	0.5215
6	0.5937	0.8594	0.5367	0.6654	0.4063	0.1406	0.4633	0.3346
7	0.3806	1.0000	0.7621	0.9796	0.6194	0.0000	0.2379	0.0204
8	0.5824	0.9595	0.7880	1.0000	0.4176	0.0405	0.2120	0.0000
9	0.4191	0.8327	0.4173	0.6730	0.5809	0.1673	0.5827	0.3270
10	0.3562	0.1266	0.4989	0.5539	0.6438	0.8734	0.5011	0.4461
11	0.2695	0.0137	0.0000	0.0000	0.7305	0.9863	1.0000	1.0000
12	0.3613	0.2884	0.5371	0.4459	0.6387	0.7116	0.4629	0.5541
13	0.6368	0.8819	0.7623	0.9087	0.3632	0.1181	0.2377	0.0913
14	0.0000	0.1493	0.1977	0.5229	1.0000	0.8507	0.8023	0.4771
15	0.8416	0.8532	1.0000	0.9500	0.1584	0.1468	0.0000	0.0500
16	0.8509	0.5676	0.9329	0.8273	0.1491	0.4324	0.0671	0.1727
17	0.2812	0.4556	0.4173	0.6674	0.7188	0.5444	0.5827	0.3326
18	0.6404	0.8757	0.8566	0.9642	0.3596	0.1243	0.1434	0.0358
19	0.2788	0.0000	0.0418	0.0324	0.7212	1.0000	0.9582	0.9676

Table 6 Sequences after data processing and deviation sequences (continued)

Exp. no.	*Sequences after data processing*				*Deviation sequences* (Δ_{ij})			
	Elegant	*Youthful*	*Modern*	*Sporty*	*Elegant*	*Youthful*	*Modern*	*Sporty*
20	0.4858	0.1287	0.5474	0.5188	0.5142	0.8713	0.4526	0.4812
21	0.3351	0.0074	0.0781	0.0492	0.6649	0.9926	0.9219	0.9508
22	0.2616	0.2427	0.3074	0.4946	0.7384	0.7573	0.6926	0.5054
23	0.9332	0.3678	0.8479	0.6392	0.0668	0.6322	0.1521	0.3608
24	0.2593	0.1639	0.2545	0.3428	0.7407	0.8361	0.7455	0.6572
25	0.3196	0.2376	0.0259	0.5411	0.6804	0.7624	0.9741	0.4589
26	1.0000	0.7344	0.9403	0.9551	0.0000	0.2656	0.0597	0.0449
27	0.4394	0.4967	0.6158	0.8173	0.5606	0.5033	0.3842	0.1827

3.2.2 Reference sequence definition

Once the grey relational generation is completed, the reference sequence is defined to determine an alternative whose comparability sequence is closest to the reference (ideal) sequence. The best alternative is produced if all of performance values are close or equal to 1. As shown in Table 6, the reference sequence X_0 is defined as $(x_{01}, x_{02}, x_{0j}, x_{0n}) = (1, 1, 1, 1)$.

3.2.3 GRC calculation

The GRC is calculated from the normalised data to determine the degree of closeness between the normalised S/N ratio x_{ij} and the reference sequence x_{0j}. A larger GRC value indicates that x_{ij} and x_{0j} are significantly close to one another. The GRC is defined by:

$$\gamma\left(x_{0j}, x_{ij}\right) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \tag{3}$$

where $\gamma(x_{0j}, x_{ij})$ is the GRC between x_{ij} and x_{0j}, $\Delta_{ij} = |x_{0j} - x_{ij}|$ is the deviation sequences,

$$\Delta_{\min} = \min\{\Delta_{ij},\ i = 1,\ 2, \ldots,\ m;\ j = 1,\ 2, \ldots,\ n\},$$

$$\Delta_{\max} = \max\{\Delta_{ij},\ i = 1,\ 2, \ldots,\ m;\ j = 1,\ 2, \ldots,\ n\},$$

and ζ is the distinguishing coefficient, $\zeta \in [0, 1]$, for compressing or expanding the range of GRCs.

In this study, the distinguishing coefficient $\zeta = 0.5$ is utilised as this value provides moderate distinguishing effects and good stability. By referring to the deviation sequences in Table 6, the GRCs for each combinative design alternative with respect to the four representative Kansei responses are determined using equation (3) and are presented in columns 2 through 5 of Table 7.

Table 7 Calculated results for GRC and GRG

Experiment no.	*GRC*				*GRG*	*Order*
	Elegant	*Youthful*	*Modern*	*Sporty*		
w_j	0.2538	0.2518	0.2487	0.2457		
1	0.3855	0.3620	0.4765	0.3597	0.3959	24
2	0.4085	0.5205	0.4094	0.4158	0.4387	19
3	0.3651	0.6175	0.5258	0.5343	0.5102	14
4	0.5052	0.5786	0.5875	0.6036	0.5683	11
5	0.3752	0.6681	0.5360	0.4895	0.5171	13
6	0.5517	0.7806	0.5191	0.5991	0.6129	9
7	0.4467	1.0000	0.6776	0.9607	0.7698	5
8	0.5449	0.9251	0.7022	1.0000	0.7916	3
9	0.4626	0.7493	0.4618	0.6046	0.5695	10
10	0.4372	0.3641	0.4995	0.5285	0.4567	18
11	0.4064	0.3364	0.3333	0.3333	0.3527	27
12	0.4391	0.4127	0.5193	0.4743	0.4611	17
13	0.5792	0.8090	0.6778	0.8456	0.7271	7
14	0.3333	0.3702	0.3839	0.5117	0.3991	23
15	0.7595	0.7730	1.0000	0.9090	0.8595	2
16	0.7703	0.5363	0.8817	0.7433	0.7325	6
17	0.4102	0.4788	0.4618	0.6005	0.4871	15
18	0.5817	0.8009	0.7771	0.9332	0.7719	4
19	0.4094	0.3333	0.3429	0.3407	0.3569	26
20	0.4930	0.3646	0.5249	0.5096	0.4727	16
21	0.4292	0.3350	0.3516	0.3446	0.3654	25
22	0.4037	0.3977	0.4192	0.4973	0.4291	20
23	0.8822	0.4416	0.7667	0.5809	0.6685	8
24	0.4030	0.3742	0.4014	0.4321	0.4025	22
25	0.4236	0.3961	0.3392	0.5215	0.4197	21
26	1.0000	0.6531	0.8933	0.9176	0.8659	1
27	0.4714	0.4984	0.5655	0.7324	0.5657	12

3.2.4 GRG calculation

The GRG is used for the overall evaluation of the S/N ratio of multiple performance characteristics by converting them into a single performance characteristic index. The GRG is calculated using the following equation:

$$\Gamma\left(X_0, X_i\right) = \sum_{j=1}^{n} w_j \gamma\left(x_{0j}, x_{ij}\right), \qquad \sum_{j=1}^{n} w_j = 1 \tag{4}$$

where $\Gamma(X_0, X_i)$ is the GRG for the i^{th} alternative (experiment), $\gamma(x_{0j}, x_{ij})$ is the GRC and w_j is the weighting value for the j^{th} criterion, $j = 1, 2, \ldots, n$.

In this study, the corresponding weighting value w_j of the j^{th} criterion is assigned using PCA based on the context of application. According to the weighting value of each Kansei response obtained from PCA in Section 3.3, the GRGs for each combinative design alternative were calculated using equation (4) and are presented in column 6 of Table 7.

3.3 Principal component analysis

PCA was introduced by Pearson and developed by Hotelling to explain the variance-covariance structure by linear combinations of each quality characteristic (Jolliffe, 2002). PCA is a method of dimensional reduction without sacrificing accuracy. In this study, PCA was specifically used to determine the corresponding weighting values of each performance characteristic so that the weighting value of each Kansei response will objectively reflect the relative importance of each performance characteristic in the GRA.

In this method, the original multiple quality characteristics are converted into a new set of uncorrelated variables known as principal component (PC) by calculating the eigenvectors of the covariance matrix of the original multiple quality characteristics. In this paper, the original multiple quality characteristics are the GRC of performance characteristics. The eigenvalues and eigenvectors are determined using the following equation (Khan et al., 2010):

$$\left(R - \lambda_k I_m\right) V_{ik} = 0 \tag{5}$$

where λ_k represents the eigenvalues and V_{ik} represents the eigenvectors corresponding to the eigenvalue λ_k.

The uncorrelated PCs can be determined using the following equation:

$$Y_{mk} = \sum_{i=1}^{n} x_m(i) V_{ik} \tag{6}$$

where Y_{m1} is the first PC, Y_{m2} is the second PC and so on.

The PCs are then sequenced in a descending order with respect to the variance, and therefore the first PC Y_{m1} accounts for the highest variance in the data.

In this paper, the GRCs shown in Table 7 were used to determine the related eigenvalues and eigenvectors using equation (5). The eigenvalues for each PC and its percentage of explained variation and cumulative variance are presented in Table 8 whereas the corresponding eigenvectors of each Kansei response for each PC and the contribution of each Kansei response to the PCs are listed in Table 9. The selection criteria for PCs are based on the PCs' contribution that has a cumulative contribution greater than 90% of the total variation (Jolliffe, 2002). Referring to Table 8, the first and second PC would be extracted since they are the first two PCs which fulfil the above criterion. These first two PCs characterise the four Kansei responses that contributed to the percentage variance value as high as 94.78%. The contribution of the respective performance characteristic (Kansei response) to the PCs is determined from squaring the eigenvector corresponding to each eigenvalue. The contributions of the four representative Kansei responses to the PCs are summarised in column 5 of Table 9, where each Kansei response has a contribution values of 0.2538, 0.2518, 0.2487 and 0.2457, respectively. These contributions were then determined as the weighting values of the appropriate performance characteristic for calculating the GRG in Section 3.2.4. As a result, the coefficients w_1, w_2, w_3 and w_4 in equation (4) were set as 0.2538, 0.2518, 0.2487 and 0.2457, respectively.

Table 8 Eigenvalues, explained variation and cumulative percentage for all PCs

PC	*Eigenvalue*	*Explained variation (%)*	*Cumulative percentage (%)*
1st	2.9990	74.98	74.98
2nd	0.7920	19.80	94.78
3rd	0.1236	3.09	97.86
4th	0.0854	2.14	100.00

Table 9 Eigenvectors and contribution of each Kansei response to the PCs

Kansei response	*Eigenvector*				*Contribution*
	1st PC	*2nd PC*	*3rd PC*	*4th PC*	
Elegant	0.4523	–0.6634	0.4449	–0.3968	0.2538
Youthful	0.4547	0.6499	0.6000	0.1043	0.2518
Modern	0.5450	–0.2568	–0.2657	0.7526	0.2487
Sporty	0.5401	0.2675	–0.6095	–0.5150	0.2457

3.4 *Determining the optimum combination of product form feature*

In this step, the GRG obtained from GRA over the form features is analysed to determine the optimum combination of product form features based on Taguchi analysis. The Taguchi analysis of GRG uses the Taguchi's OA property to separate the effect of each form feature on the GRG at different levels. The Taguchi analysis converts each GRG by averaging the GRG value for each experiment level of the corresponding form feature into the response table of form features and levels on the averaged GRG. The optimum combination of product form features is then selected according to each form features level with the highest GRG identified based on Taguchi analysis.

In this paper, the Taguchi analysis of GRG obtained for 13 form features was performed using Taguchi's L_{27} OA. Based on the GRG in column 6 of Table 7, the average GRG for each form feature level and the total mean GRG for 27 design experiments (alternatives) are calculated into the response table of GRG. Table 10 shows the response table of GRG for each form feature level and its factor effect. The factor effect is the difference of the average GRG between the maximum and minimum level for each product form feature. The average GRG for each form feature level shown in Table 10 are also presented graphically in Figure 2.

3.5 *Analysis of variance*

ANOVA is used to investigate the product form features which have the most significant contribution on the performance characteristic. In this paper, ANOVA is achieved by separating the total variability of the GRGs which is calculated by the sum of the squared deviations from the total mean of the GRG, into contributions by each product form feature and the error. The ANOVA results of the GRG are summarised in Table 11.

Table 10 Response table of form features and levels on averaged GRG

Symbol	*Form feature*	*GRG Level 1*	*GRG Level 2*	*GRG Level 3*	*Effect*
A	Ratio of car height to car length	0.5749	0.5831[a]	0.5052	0.0779
B	Ratio of fore region length to overall length	0.4234	0.5760	0.6247[a]	0.2014
C	Ratio of front height to overall height	0.5374	0.5356	0.5902[a]	0.0546
D	Gradient of front bumper	0.5758[a]	0.5427	0.5446	0.0330
E	Gradient of hood	0.5395	0.5548	0.5687[a]	0.0292
F	Gradient of A-pillar	0.6482[a]	0.5553	0.4597	0.1885
G	Ratio of rear region length to overall length	0.4785	0.5606	0.6240[a]	0.1455
H	Ratio of rear region height to overall height	0.5810[a]	0.5440	0.5382	0.0428
I	Gradient of C-pillar	0.5734[a]	0.5533	0.5364	0.0370
J	Gradient of rear bumper	0.5673[a]	0.5327	0.5631	0.0346
K	Gradient of trunk	0.5224	0.5623	0.5784[a]	0.0561
L	Gradient of rear fender bottom	0.4947	0.5677	0.6007[a]	0.1059
M	Gradient from side top	0.5652	0.5653[a]	0.5325	0.0328
The total mean value of GRG = 0.5544					

Note: [a]Maximum feature level.

Figure 2 Graphical representation of GRG (see online version for colours)

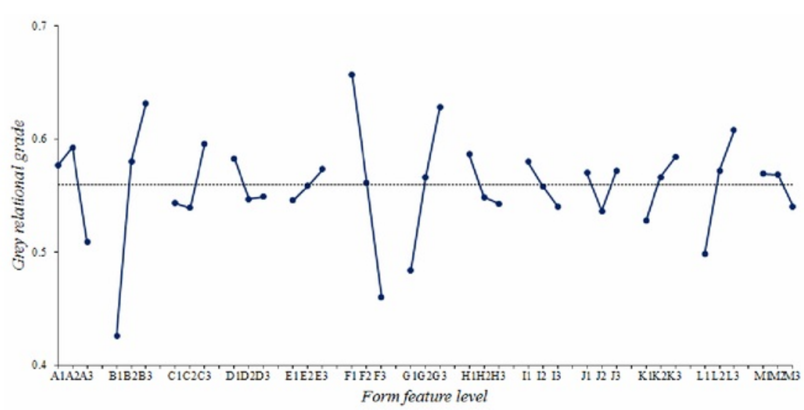


Table 11 ANOVA results of GRG

Symbol	*Form feature*	*DF*	*SS*	*MS*	*F-value*	*Cont. (%)*
A	Ratio of car height to car length	2	0.0330	0.0165	2.8921	4.82
B	Ratio of fore region length to overall length	2	0.2032	0.1016	17.8183	29.70
C	Ratio of front height to overall height	2	0.0173	0.0087	1.5177	2.53
D	Gradient of front bumper	2	0.0062	0.0031	0.5429	0.90
E	Gradient of hood	2	0.0038	0.0019	0.3367	0.56
F	Gradient of A-pillar	2	0.1599	0.0800	14.0203	23.37
G	Ratio of rear region length to overall length	2	0.0958	0.0479	8.3987	14.00
H	Ratio of rear region height to overall height	2	0.0097	0.0049	0.8524	1.42
I	Gradient of C-pillar	2	0.0062	0.0031	0.5412	0.90
J	Gradient of rear bumper	2	0.0064	0.0032	0.5620	0.94
K	Gradient of trunk	2	0.0150	0.0075	1.3153	2.19
L	Gradient of the rear fender bottom	2	0.0529	0.0264	4.6379	7.73
M	Gradient from side top	2	0.0064	0.0032	0.5644	0.94
	Error	12	0.0684	0.0057		10.00
	Total	38	0.6843			100.00
	$F_{0.05(2,12)} = 3.88$					

Notes: DF = degree of freedom; SS = sum of square; MS = mean square; MS = mean square; Cont. = contribution.

4 Results and discussion

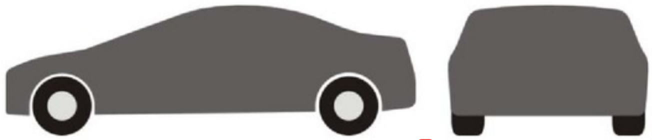
The grey PCA-based TM method was used to determine the optimum combination of product form features according to the multiple Kansei responses. This hybrid method was used to overcome the shortcoming of traditional TM which can only be utilised for a single-response optimisation problem. The GRA is integrated with TM to simplify the optimisation process by converting the complicated multiple performance response values into single performance response index, the GRG. The PCA is intended to solve the subjectivity in assigning the weighting values for each performance response. A car form design silhouette is used as an illustrative case study in order to demonstrate the applicability of this hybrid method.

In the process of determining the optimum combination of car form features in multi-response problem, the S/N ratio analysis was performed to transform the evaluation values obtained from the Taguchi experiments into S/N ratio of multiple Kansei responses (Table 5). For overall evaluation of the multiple Kansei response, GRA synthesises the S/N ratio of multiple Kansei responses into a single GRG (Table 7). At the same time, PCA was carried out to determine the weighting values of each Kansei response representing the contribution or relative importance of each Kansei response to the GRG (overall performance). In past studies, the corresponding weighting value for each performance characteristic is often assumed to be equal or assigned by the decision-makers' subjective estimations (Acherjee et al., 2011; Kuo et al., 2008; Kuram and Ozcelik, 2013). PCA is used in this study to objectively assign the weighting values of each performance characteristic (Kansei response) into the GRA to calculate the GRG. The weighting values of each performance characteristic are the square of the eigenvectors of the selected PCs. According to Table 9, the contribution or relative importance of each Kansei responses (i.e., elegant, youthful, modern, and sporty) were 0.2538, 0.2518, 0.2487 and 0.2457, respectively. This shows that PCA was able to objectively reveal the contribution or relative importance of each Kansei response to overall performance. These contributions and GRCs were then used to calculate the GRG, as presented in Table 7, showing that the complicated multiple Kansei responses can be converted to a single GRG. The optimisation process has effectively performed and was able to generate a single GRG rather than complicated performance responses.

The traditional approach in TM for solving multiple-response problem would involve separate evaluation of form feature levels corresponding to each response. However, optimising Kansei responses in a separated manner may lead to a serious conflict and bring the complexity of the feature's setting in a multi-response problem (Hsieh et al., 2005). Another approach is to rely on engineering judgement as the primary method when solving the multi-response problem in the traditional TM (Jeyapaul et al., 2005). However, the judgement of an engineer or a designer may increase the uncertainty during the decision-making process. Hence, this hybrid method is less complicated than the traditional TM for solving multi-response optimisation decision-making problem and has the ability to obtain the optimum form features combination in the multi-response problem while minimising the variations in product form perceptions among different consumer evaluations.

From the GRG in Table 7, it can be seen that design alternative (experiment) nos. 26, 15, 8, 18 and 7 have high GRG, indicating that these design alternatives are close to the best multiple performance responses among the 27 design alternatives. However, these findings could not be used immediately to decide the optimum combination of car form features. Hence, Taguchi analysis of the GRG over 13 form features using Taguchi's L_{27} OA was conducted to select the optimum combination of car form features. Table 10 shows the Taguchi analysis response table of the average GRG for each form feature level and its factor effect. A greater factor effect indicates that the car form feature has a significant influence to the GRG. A higher GRG value implies better multiple performance characteristics. Consequently, the level with the highest average GRG indicates the best multiple performance characteristics. Thus, the combination of car form features which results in the highest average GRG would be the optimum combination. The optimum form feature combination was determined from the response table of GRG in Table 10 and the graphical representation of GRG in Figure 2. The car form feature levels yielding the maximum average GRG are A_2, B_3, C_3, D_1, E_3, F_1, G_3, H_1, I_1, J_1, K_3, L_3 and M_2. These form feature levels are therefore selected as the optimum combination of car form features that looks and feels elegant, youthful, modern and sporty in a single form design. A car form silhouette of this optimised form design is depicted in Figure 3.

Figure 3 Car form design corresponding to optimum combination of form features



ANOVA was conducted to identify the form feature which significantly influences the performance characteristics of the optimised form design. An ANOVA of the GRG (Table 11) shows that form features B, F, G, L and A have significant contributions with values of 29.70%, 23.37%, 14.00%, 7.73% and 4.82%, respectively. These form features are significant as the F-values of each these form feature are greater than 3.88 which is the critical $F_{0.05(2,12)}$ value obtained from the Fisher's F-test. The contributions of the remaining form features (i.e., C, K, H, J, M, D, I and E) were 2.53%, 2.19%, 1.42%, 0.94%, 0.94%, 0.90%, 0.90% and 0.56%, respectively. Thus, the form features B, F, G, L and A, with a total contribution of 79.62%, are the car form features which have a major influence on the performance characteristics of the optimised form design. In addition, the experiments possess high feasibility and sufficiency as the percentage of contribution error is around 10%, as shown in Table 11. An experiment is considered as acceptable without neglecting major factors if the percentage of error is less than 15%, whereas the experiment is considered as unacceptable with a loss of significant factors if the percentage of error exceeds 50% (Huang et al., 2006; Lu et al., 2009). Hence, it can be concluded that the grey PCA-based TM is highly acceptable.

5 Conclusions

This paper presents the application of a hybrid method, grey PCA-based TM, to solve a multi-response optimisation decision-making problem for determination of the optimum combination of product form features in KE. A case study on optimising the multiple Kansei responses of a car form design was used to demonstrate the application of this method. This hybrid method was able to solve the complexity trade-off faced in the decision-making process of the multi-response optimisation in KE. It is also able to deal with the conflict between the optimum combination levels suggested by the various Kansei responses using an economical and effective experimental design solution. The experiment result shows that the hybrid method was successfully able to determine the optimum combination of product form features and to systematically generate an optimised car form design which accommodates the multiple Kansei needs of consumers. Accordingly, this hybrid method is advantageous as it is straightforward to implement, involves relatively simple procedures and does not require a large number of experiment samples and time-consuming experiments. Thus, this method reduces the time and cost required in the product design and development process. Although in this paper the method is only shown for optimising a car form design, it can be upscaled for applications in global product design problems. This is a useful tool for designers in solving multi-response optimisation decision-making problems in KE, in order to obtain optimum design solutions for such problems. The limitation of this method is that this approach would be difficult to apply on a totally new product that has yet to be introduced in the market, where customers will not have prior awareness of the product features, making the survey difficult to conduct or irrelevant.

Future development of the method may consider the contribution of demographic characteristics to the optimum design solutions. In addition, confirmatory and benchmarking tests can be conducted by comparing the results obtained using this hybrid method with other popular methods available.

Acknowledgements

The authors would like to acknowledge the Japan International Cooperation Agency (JICA) for supporting this research under the AUN/SEED-Net project Grant No. JICA 8123227. The first author gratefully acknowledges the financial support provided by the Malaysian Ministry of Higher Education (MOHE) under the HIR Grant No. UM.C/HIR/MOHE/ENG/08 (D000008-16001).

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